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A pBCI to Predict Attentional Error Before it Happens in Real Flight Conditions

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Abstract— **Accident analyses have revealed that pilots can fail to process auditory stimuli such as alarms, a phenomenon known as inattentional deafness. The motivation of this research is to develop a passive brain computer interface that can predict the occurence of this critical phenomenon during real flight conditions. Ten volunteers, equipped with a dry-EEG system, had to fly a challenging flight scenario while responding to auditory alarms by button press. The behavioral results disclosed that the pilots missed 36% of the auditory alarms. ERP analyses confirm that this phenomenon affects auditory processing at an early (N100) and late (P300) stages as the consequence of a potential attentional bottleneck mechanism. Inter-subject classification was carried out over frequency features extracted three second epochs before the alarms' onset using sparse representation for classification (SRC), sparse and dense representation (SDR) and more conventional approach such as linear discriminant analysis (LDA), shrinkage LDA and nearest neighbor (1-NN). In the best case, SRC and SDR gave respectively a performance of 66.9% and 65.4% of correct mean classification rate to predict the occurrence of inattentional deafness, outperforming LDA (60.6%), sLDA (60%) and 1-NN (59.6%). These results open promising perspectives for the implementation of neuroadaptive automation with as ultimate goal to enhance alarm stimulation delivery so that it is perceived and acted upon.**

I. INTRODUCTION

Operating aircraft is a demanding activity that involves the management of multiple visual (e.g. monitoring the flight parameter) and auditory tasks (e.g. radio communication) in a dynamic and uncertain environment [1], [2], [3]. Distribution of attention is a key issue for piloting and relies on a trade-off between focused attention (eg. performing a check-list) to avoid distraction, and diffused attention to detect unexpected changes (eg. failure). These top-down and bottom-up types of attention are respectively supported by the dorsal and ventral neural networks that are in close interaction [4]. However, when task demand exceeds mental capacity, the homeostasis between these two neural pathways could be disrupted, leading to an impaired processing of unexpected stimuli [5], [6]. Although this shielding mechanism can prevent mental overload, missing critical information can jeopardize flight safety [7]. For instance, accident analyses [8] and experiments conducted in flight simulators [9], [10], [11] reported that auditory alarms could fail to reach awareness when engaged under demanding cognitive flying tasks. This phenomenon, known as inattentional deafness, has been shown to take place at an early stage of auditory processing [12] through top-down inhibitory mechanisms implemented via the activation of cortical regions associated with an attentional bottleneck [13]. Complementary evidence of this phenomenon was supported by an electrophysiological experiment conducted in real flight conditions which revealed that a reduction in phase resetting in alpha and theta band frequencies was a neural signature of inattentional deafness to auditory alarms [14].

A relevant approach to improve flight safety is to implement passive brain computer interfaces (pBCI) or neuro-adaptive technology [15], [16], [17], [18] to continuously monitor pilots' attentional state and to detect the possible occurrence of degraded states. Recently, [12] implemented an offline pBCI to detect inattentional deafness to auditory alarms during a simulated flight. Such an approach opens promising perspectives for pilot-cockpit interaction, however a step further would be to predict rather than detect episodes of inattentional deafness [20]. As a consequence, one could imagine the design of a smart cockpit that would implicitly adapt itself to the pilots' attentional state with a set of counter-measures.

To meet this challenging goal, supervised dictionary learning approach has been shown to be an efficient means to lead state-of-the-art results in many applications including signal classification [21]. Indeed, in recent years there has been a growing interest in the use of techniques such as sparse representation for classification (SRC) or sparse and dense representation (SDR) in order to build discriminative representations by minimizing the intra-class homogeneity, maximizing class separability and promoting sparsity for more generalization ability [22], [23], [24]. This is done by learning a dictionary per class and making them dissimilar by boosting the pairwise orthogonality. When compared to conventional dictionary learning techniques [25] which they solely try to minimize the reconstruction error, supervised dictionary learning has the merit to be a very efficient way to classify EEG signals for BCI purposes [26], [27].

The objective of the present study was to develop a pBCI to predict auditory alarm misperception in the context of flying. Participants were asked to perform a demanding flying scenario along with an auditory alarm detection task in real flight conditions. In line with previous studies, we used dry-electrode EEG that has proven to be suitable for measuring

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Fig. 1. Left: ISAE-SUPAERO DR400 aircraft. Right: EEG dry electrode Enobio system used for the experiment

brain response [14], [28] and to perform single trial classification [29], [30], [31], [32] in actual flight conditions. We proposed to use SRC as well as SDR techniques to predict inattentional deafness with frequency features computed over the EEG signal in a 3-second time-window preceding the onset of each auditory alarm. More conventional approaches including Nearest Neighbor (1-NN), Linear Discriminant Analysis (LDA) and shrinkage Linear Discriminant Analysis (sLDA) were also used as a benchmark.

II. Methods

A. Experimental protocol

Ten pilots were recruited among the students of the ISAE-SUPAERO engineering school to participate in the study (10 males; 25- 48 years old, with 40-230 flight hours experience). All had normal or corrected-to-normal vision and no history of neurological or psychiatric disorders. The study was approved by the European Aviation Safety Agency (EASA60049235) and all participants gave their informed written consent.

1) Experimental environment: DR400 aircraft: The study was conducted using the ISAE-SUPAERO (Institut Supérieur de l'Aéronautique et de l'Espace - French Aeronautical University in Toulouse, France) experimental DR400 light aircraft (see Fig 1). The DR400 light aircraft was powered by a 180HP Lycoming engine and was equipped with classical gauges, radio navigation equipment, and actuators such as rudder, stick, thrust and switches to control the flight. A switch button was attached to the stick to collect the pilots response to auditory alarms.

2) Scenario: The experiment lasted approximately one hour in duration and involved navigation tasks, diversions, simulated engine failure exercises, and series of touch-and-go (landings and takeoffs) involving low altitude circuits patterns. Along with the flying task, the participants had to perform an auditory oddball detection task with a total of 1000 auditory stimuli: 25% were alarm stimuli (250 normalized pure tone at 1100 Hz, 90 dB SPL) and 75% were non-alarm stimuli (750 normalized pure tone at 1000 Hz, 90 dB SPL). The inter-trial interval was set to 3000 ms with a 2000-ms jitter. The participants were instructed to respond quickly by pushing a button attached to the flight control stick after hearing the alarm stimuli. The auditory task started during takeoff and would end before or during landing.

3) Experimental protocol: The participants were first trained to perform the auditory task alone for five minutes while seated in a calm room at ISAE-SUPAERO hangar. After completing the auditory task, they were equiped with the 30 dry electrode Enobio EEG cap. The volunteers wer then left-seated on the aircraft and had to wear a Clarity Aloft headset that was used to trigger auditory stimuli from a PC via an audio cable. The participants could still communicate with the other crew members and the air traffic controllers when they received auditory alarms. The safety pilot was right seated and had the authority to stopping the experiment and taking over the control of the aircraft for any safety reason. The backseater was the experimenter: his role was to set the sensor, to trigger the experimental scenario and to supervise data collection.

4) Data recording: EEG data were recorded at 500 Hz using the 30 dry-electrode Enobio Neuroelectrics system positioned according to the 10-20 system. We used Lab Streaming Layer libraries (LSL, Swartz Center for Computational Neuroscience, UCSD, November 2018) to synchronize the oddball task in Matlab (Ver. 2017.b) and the response button with the Enobio acquisition software (NIC V2.0). The data were processed using EEGLab (Ver. 15).

5) Event Related Potential (ERP) and Frequency domain analysis with sLoreta: Similarly to [14], we computed ERP over Cz electrode. Our motivation was to check that we actually picked brain signals and that the N100 and P300 amplitudes were lower for misses that hits as demonstrated by [12]. To do so, the continuous EEG data was filtered between 0.5–30 Hz (windowed-sinc FIR filter with an order of 250). Noisy portions of data (e.g., trials) were cleaned using the Artifact Subspace Reconstruction (ASR) [33]. Independent component analysis (ICA) was then ran over the filtered data and IClabel Label function was used to keep only brain components. The epochs for auditory misses and hits were extracted from the continuous data 0.2 s before and 1 s after stimuli onsets. The trials used for the ERP analyses were baseline normalized using data from 200 to 0 ms prior to the stimulus onset. We also ran descriptive frequency domain analyses using sLoreta over three second epochs extracted before the alarms' onset. The objective was to localize and identify potential neural mechanisms that could predict alarm misperception. To do so, we used the same pipeline described previously to the exception that the data were epoched starting 3000 ms before and ending 0 ms before the auditory misses and the auditory hits.

III. Classification

1) EEG processing pipeline for classification purpose: The signal was first epoched starting 3000 ms before and ending 0 ms before the auditory alarms (see figure 2). Each epoch was then high-passed (0.5 Hz). Noisy portions of epoched data were cleaned using ASR. The ASR filter was calibrated using the first 30 s of EEG recording that were not used for the classification. Frequency based features were computed for each trial in the delta [1 4], theta [4 8] Hz, alpha [8 12] Hz, beta [12 30] Hz and gamma [30 80] Hz bands using a 250-order windowed sinc FIR-filter trial. Eventually, we computed an EEG engagement ratio $\frac{\beta+\gamma}{\alpha+\theta}$ adpated from [36].

A. Sparse representation for classification

Let us consider $\{(\mathbf{x}_j, y_j)\}_{j=1}^{n}$ where $\mathbf{x}_j \in \mathbb{R}^m$ be signal and $y_j \in \{1, \cdots, c\}$ be its class label. We consider a class based dictionary $\{\mathbf{D}_i\}_{i=1}^{c} \in \mathbb{R}^{m \times n_i}$ the n_i training samples associated to class i. The global dictionary $\mathbf{D} = [\mathbf{D}_1 \cdots \mathbf{D}_c] \in \mathbb{R}^{m \times n}$ represents the concatenation of the class based dictionaries $\{\mathbf{D}_i\}_{i=1}^{c}$. The sparse representation of a test sample $\mathbf{p}$ over the global dictionary $\mathbf{D}$ noted $\boldsymbol{\alpha}^T = [\boldsymbol{\alpha}_1^T \cdots \boldsymbol{\alpha}_i^T \cdots \boldsymbol{\alpha}_c^T]$ is given by:

$$\min_{\boldsymbol{\alpha}} \frac{1}{2} \|\mathbf{p} - \mathbf{D}\boldsymbol{\alpha}\|_2^2 + \lambda \|\boldsymbol{\alpha}\|_1 \quad (1)$$

where $\|.\|_1$ denotes the ℓ_1-norm corresponding to the absolute sum of the vector $\boldsymbol{\alpha}$, λ is a parameter controlling the compromise between the reconstruction error and sample-wise sparsity and $\boldsymbol{\alpha}$ represents the sparse representation over the global dictionary $\mathbf{D}$.

With the assumption that subspaces of distinct classes are independent to each other, the formulation (1) achieves a discriminative representation where significant nonzero coefficients are only associated to the correct subject. Thus the resulting sparse representation in (1) named in the literature Sparse Representation for Classification (SRC) [39] is suitable for classification. The classification is performed by computing residual reconstruction error of the test sample $\mathbf{p}$ using the training samples of each class i serving as a dictionary $\mathbf{D}_i$ and their corresponding sparse coefficients $\boldsymbol{\alpha}_i$ as follows:

$$e_i = \|\mathbf{p} - \mathbf{D}_i\boldsymbol{\alpha}_i\|_2^2 \quad i = 1, \cdots, c \quad (2)$$

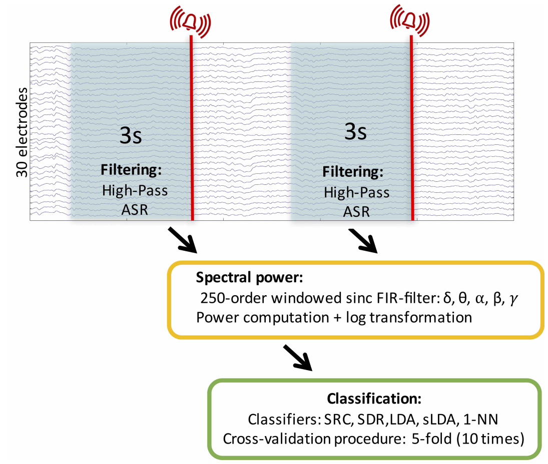

Fig. 2. Classification pipeline

The class label of the given test sample is assigned to class i that minimizes the reconstruction error using $\mathbf{D}_i$ and $\boldsymbol{\alpha}_i$.

B. Sparse and dense hybrid representation

Despite of the impressive results of SRC, a number of works put in doubt its effectiveness for classification [48] [47]. To solve this problem, it has been proposed to separate the class-specific information from others to allow the sparse representation of the query signal to coincide with the correct classification target specified by the class labels of the training data. Therefore, a query EEG signal $\mathbf{p}$ is decomposed into three main components as follows:

$$\mathbf{p} = \mathbf{a} + \mathbf{b} + \mathbf{s} \quad (3)$$

where $\mathbf{a}$ is the class-specific component, $\mathbf{b}$ the non-class-specific variations and $\mathbf{s}$ contains random sparse noise.

Lets $\mathbf{A}$ a dictionary containing only class-specific component, the sparse representation $\boldsymbol{\alpha}$ of the class-specific component of the query signal $\mathbf{p}$ can be computed using SRC as follows:

$$\mathbf{a} = \mathbf{A}\boldsymbol{\alpha} + \mathbf{e}_a \quad (4)$$

the sparse vector $\boldsymbol{\alpha}$ of (4) will directly coincide with the class label of the query signal $\mathbf{p}$ as the both $\mathbf{a}$ and $\mathbf{A}$ only contain the class-specific information.

Unfortunately, separating the class-specific component $\mathbf{a}$ from a single unknown query signal $\mathbf{p}$ is a very challenging problem if not impossible. To address this problem, a non-class-specific representation $\mathbf{z}$ is defined by the dictionary $\mathbf{B}$ containing non-class-specific information as follows:

$$\mathbf{b} = \mathbf{B}\mathbf{z} + \mathbf{e}_b \quad (5)$$

the component $\mathbf{b}$ does not contribute in the classification and hence $\mathbf{z}$ in (5) is defined as dense representation. The summation of (4), (5) and $\mathbf{s}$ yields the hybrid sparse-and-dense representation (SDR) [45] of the query signal as follows:

$$\mathbf{p} = \mathbf{A}\boldsymbol{\alpha} + \mathbf{B}\mathbf{z} + \mathbf{e} \quad (6)$$

where $\mathbf{e} = \mathbf{e}_a + \mathbf{e}_b + \mathbf{s}$ is the combined representation error.

To represent a query signal $\mathbf{p}$, every training sample only uses its class-specific component to compete against the others collaboratively with the non-class-specific component of all training samples. As $\boldsymbol{\alpha}$ represents the class-specific information and contributes in the classification through a sparse minimization, it is chosen sparse. In the other hand, $\mathbf{z}$ stands for the non-class specific and does not contribute in the classification, as consequence is taken dense. The solution of the SDR, $\boldsymbol{\alpha}$, $\mathbf{z}$ and $\mathbf{e}$ is obtained by solving the following optimization problem [45]:

$$\begin{cases} \min\limits_{\boldsymbol{\alpha},\mathbf{z},\mathbf{e}} \|\boldsymbol{\alpha}\|_1 + \beta \|\mathbf{z}\|_2^2 + \gamma \|\mathbf{e}\|_1 \\ \\ \text{s.t} \quad \mathbf{p} = \mathbf{A}\boldsymbol{\alpha} + \mathbf{B}\mathbf{z} + \mathbf{e} \end{cases} \tag{7}$$

the optimization problem (7) can be solved by the Augmented Lagrange Multiplier (ALM) scheme [46].

The representation of a query signal $\mathbf{p}$ by the class-specific component of class i and the non-class-specific component of all classes collaboratively is given by:

$$\mathbf{p} = \mathbf{A}\mathbf{L}_i\boldsymbol{\alpha} + \mathbf{B}\mathbf{z} + \mathbf{e}_i \tag{8}$$

where $\mathbf{L}_i \in \mathbb{R}^{n\times n}$ is a selection operator given by

$$\begin{cases} \mathbf{L}_i(k,k) = 1 \quad \text{if } k^{th} \text{ training} \in \text{class } i \\ \\ 0 \qquad \text{otherwise} \end{cases} \tag{9}$$

The class-wise representation residual is defined by:

$$r_i(\mathbf{p}) = \|\mathbf{e} - \mathbf{e}_i\|_2 = \|\mathbf{A}(\mathbf{I} - \mathbf{L}_i)\boldsymbol{\alpha}\|_2 \tag{10}$$

where $\mathbf{I}$ is an identity matrix. The query signal $\mathbf{p}$ is classified into the class that produces the minimum residual $r_i(\mathbf{p})$.

It is very difficult if not impossible to decompose a single signal $\mathbf{p}$ into a class-specific component $\mathbf{a}$ and a non-class-specific component $\mathbf{b}$. However, given a labeled training database $\mathbf{D}$, it is possible to decompose it into a class-specific dictionary $\mathbf{A}$, a non-class-specific dictionary $\mathbf{B}$ and a random sparse noise $\mathbf{E}$ based on machine learning from the labeled training database. The underlying principle is that the both dictionaries $\mathbf{A}$ and $\mathbf{B}$ must be low rank matrices. We can first initialize $\mathbf{A}$ by a very low rank matrix, for example, a matrix that contains the class means of all classes. Then we can gradually transfer more information from $\mathbf{D}$ to $\mathbf{A}$ so that after training, the class-specific dictionary $\mathbf{A}$ will contain much more class-specific information than just class means. This can be done by the iterative low rank matrix decomposition of $\mathbf{A}$ and $\mathbf{B}$ from $\mathbf{D}$. It utilizes the low rank matrix recovery to transfer information from the supervised assigned dictionary $\mathbf{B}$ to $\mathbf{A}$. More details can be found in [45].

C. Classification pipeline

As explained in the section II-A.2, our participants faced 25% of auditory alarms and 75% of non-alarm stimuli. Our behavior results disclosed that our participants missed 36% of the 25% presented alarms stimuli. For classification purpose, we then used 1400 recorded EEG signals (i.e. 3s epoch before the auditory alarms): 700 miss alarms and 700 hit alarms. An equivalent number of misses and hits were selected for each participant. To avoid the dependency of the classification techniques to a specific training / testing set, we evaluate the robustness using different training and testing set, as a consequence we have divided our initial data into $L = 10$ different training and testing set. Supervised Dictionary techniques such as SRC as well as SDR were tested over the different extracted frequency features separately or all together. We then benchmarked their performance with more conventional approaches including Nearest Neighbor (1-NN), Linear Discriminant Analysis (LDA) and shrinkage Linear Discriminant Analysis (sLDA).

IV. Results

A. Electrophysiological results

At the group level (see figure 3 left), statistical analyses disclosed lower N100 and P300 amplitude for the auditory misses than hits over Cz electrode (p = 0.01 bootstrap statistics with FDR for multiple comparisons). Descriptive analyses using sLoreta, ran over 3 second epochs preceding the alarms, disclosed that audio misses relative to hits had lower oscillatory activity in the low alpha band in the right inferior frontal gyrus (see figure 3 right) but also in the right middle frontal gyrus and the right insula.

B. Classification results

Inter-subject classification accuracy using different features as well as algorithms is depicted in Table I. It can be seen that the best results were obtained using all aggregated features.

V. Discussion

The objective of this paper was to implement an EEG based pBCI to predict inattentional deafness to auditory alarms in aviation. This goal was challenging as the EEG data were collected in a real flight conditions. The behavioral results revealed that our participants missed 36% of auditory alarms on average, confirming that such a phenomenon could take place in the cockpit [10], [9], [14], [13]. ERPs analyses over Cz electrode disclosed that this phenomenon takes place at a perceptual (N100) and attentional (P300) level as previously demonstrated in flight simulator [12]. Descriptive analyses using sLoreta indicated lower alpha oscillatory activity in brain regions generally involved in attentional bottleneck processing including the inferior frontal gyrus, the insula and the superior medial frontal cortex [42]. As higher alpha oscillation are thought to reflect inhibition mechanisms, lower alpha oscillation preceding misses may suggest, on the contrary, greater activation of the attentional bottleneck to prevent the processing of incoming alarms [14].

TABLE I

INTER-SUBJECT CLASSIFICATION ACCURACY.

Methods	Features						
	Delta	Theta	Alpha	Beta	Gamma	Engagement	Fusion
1-NN	59.08 ± 3.29	57.29 ± 2.85	57.38 ± 4.06	58.21 ± 2.15	59.50 ± 3.01	58.04 ± 1.76	59.60 ± 2.70
LDA	60.20 ± 4.15	59.60 ± 2.79	58.71 ± 2.25	58.67 ± 3.06	58.50 ± 3.60	62.20 ± 2.50	60.60 ± 4.00
sLDA	60.75 ± 3.64	54.38 ± 3.45	53.38 ± 3.13	53.96 ± 3.20	56.25 ± 2.56	59.25 ± 3.33	60.00 ± 3.07
SDR	61.50 ± 3.50	62.60 ± 2.80	60.50 ± 1.80	60.40 ± 1.80	58.90 ± 1.60	62.50 ± 3.07	65.40 ± 2.80
SRC	65.60 ± 4.02	64.58 ± 2.25	63.83 ± 3.37	63.96 ± 3.42	64.08 ± 3.78	63.58 ± 2.94	66.90 ± 3.10

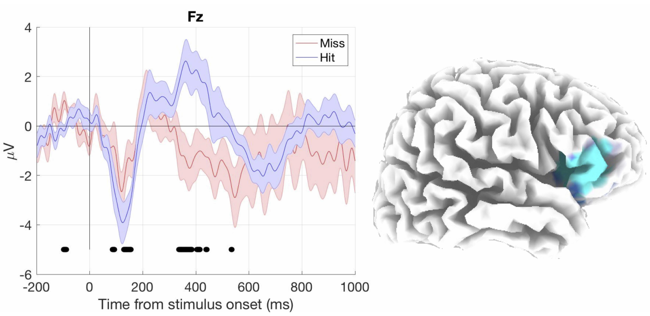

Fig. 3. Left: Grand averaged waveforms of the ERPs for Fz with standard error. The black lines on the x axis specify the time range when the auditory misses and hits related ERPs amplitudes were significantly different (*p* = 0.01, corrected). Right: Frequency domain EEG source analysis using sLoreta. Lower alpha oscillatory activity in the right inferior frontal gyrus during misses than auditory hits.

Our classification results showed that the mean prediction accuracy rate reached almost 67% in the best case with SRC. This performance is close to the 70 % accuracy defined as a sufficient accuracy for BCI [41]. The use of supervised dictionary learning approach seems to outperform more conventional techniques such as 1-NN and LDA/sLDA (60%). These latter results are consisent of our previous study with shrinkage LDA [20] which had 58% mean accuracy to predict the onset of inattentional deafness in simulated conditions. Moreover, this prior study considered intra-subject but not inter-subject classification as was used in the present study. Therefore, these findings show that our approach is a well-suited method for processing EEG signal as previously demonstrated by [26], [27]. Moreover, the performance obtained here with inter-subject classification and a dry-EEG system is altogether quite high in a general manner, but also very promising in its robustness to inter-subject variability and to ecological settings.

Taken together, these findings open good prospects for the implementation of a smart cockpit that would adapt to the user's state. For instance, one could imagine that the modality (e.g. tactile, visual) of the alarm could be optimized to increase the likelihood of reaching pilot's awareness. Another possibility would be to consider adaptive autonomy and to lower the pilots' engagement by giving more authority to the autoflight system to reduce their workload. Nonetheless, there is a need to improve the accuracy of this pBCI before it could be implemented into real cockpits. Future research should investigate other metrics such as connectivity features that have been shown to efficiently predict long term attentional performance [43]. Another possible approach would be to apply adaptive mixture independent component analysis to identify different brain network associated with auditory misses and hits, as it has previously been shown to identify brain dynamics underlying attention fluctuation in driving [44].

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